WHAT IS CLAIMED IS:

1. A process controller comprising:
controller variable inputs comprised of measurements of process variable inputs of the process being controlled;
a dynamic predictive model, of the process being controlled, with dynamic predictive model parameter(s), for receiving current variable input values wherein the dynamic predictive model parameter(s) change(s) dependent on said variable input values received by the controller; and
output(s) from the dynamic model for generating controller outputs for effectuating change to the process being controlled.

2. The controller of claim 1 wherein the dynamic predictive model is further comprised of:
a physical model with physical model parameters; and
an empirical model which adjusts the physical models parameters based on the controller variable inputs.

3. The controller of claim 2 wherein the empirical models adjustments to the physical models parameters based on the controller variable inputs is further based on historical controller inputs.

4. The controller of claim 2 where the physical model is a first principles model of the process being controlled.

5. The controller of claim 2 where the empirical models is non-linear model.

6. The controller of claim 2 where the non-linear model is a neural network.

7. The controller of claim 2 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the controller variable inputs.

8. The controller of claim 7 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the current controller variable inputs.

9. The controller of claim 7 wherein the physical model is a first principles model of the process being controlled and the empirical model is a non-linear neural network that adjusts the parameters of the first principle model based on the current and historical controller variable inputs.

10. A process control system comprising:

a distributed control system that further comprises:

a computing device operable to execute a first software tool that identifies variable inputs including at least one manipulated variable input and controlled variables associated with the process, wherein said first software tool is further operable to determine relationships between said variable input(s) and said controlled variables; and at least one controller operable to monitor said variable input parameter(s) and tune said manipulated variables.

11. The process control system of claim 10, wherein said relationships between said variable input(s) and said controlled variables comprises a first principle model(s) with model parameters wherein said first principle model parameter values are dependent on said variable input(s).

12. The process control system of claim 10, further comprising neural networks utilized to identify said model parameters.

13. The process control system of Claim 10, wherein said step of determining relationships between said variable input(s) and said controlled variables utilizes a neural network.

14. The process control system of claim 10, wherein said step of determining the relationship between said variable inputs and said controlled variables utilizes a combination of physical models and empirical methods.

15. The process control system of claim 13 wherein said physical models and empirical methods are combined in parallel and/or in series.

16. The process control system of claim 13 wherein said physical model parameter(s) varies over an operating range.

17. The process control system of claim 14 wherein said physical model is a function of said variable input(s).

18. The process control system of claim 16 wherein said physical model comprises first principle parameters which vary with said variable input(s), wherein empirical methods comprise a neural network used to identify first principle parameter values associated with said variable input(s) and wherein said neural network updates said first principle parameters with values associated with said variable input(s).

19. The process control system of claim 18 wherein said neural network is trained.

20 The process control system of claim 18 wherein said neural network is trained according to at least one method selected from the group consisting of: gradient methods, back propagation, gradient-based nonlinear programming

methods, sequential quadratic programming, generalized reduced gradient methods, and non-gradient methods.

21. The process control system of claim 20 wherein gradient methods require gradients of an error with respect to a weight and bias obtained by numerical derivatives.

22. The process control system of claim 20 wherein gradient methods require gradients of an error with respect to a weight and bias obtained by analytical derivatives.

23. The process control system of claim 10 wherein said control variable comprises a magnetic field strength, shape, location and/or orientation and said controlled variable comprises particle positions within a particle accelerator.

24. The process control system of claim 23 wherein a step of tuning the control variable comprises adjusting a connector magnet and/or quadrapole magnet.

25. A dynamic process controller predicting a change in the dynamic variable input values to the process to effect a change in the controlled variable output of the process from a current controlled variable output value at a first time to a different and desired controlled variable output value at a second time, comprising:

a dynamic predictive model for receiving the current variable input value, wherein said dynamic predictive model changes dependent upon said variable input value, and the desired controlled variable output value, and wherein said dynamic predictive model produces a plurality of desired controlled variable input values at different time positions between the first time and the second time to define a dynamic operation path of the process between the current controlled variable output value and the desired controlled variable output value at the second time; and

an optimizer for optimizing the operation of the dynamic controller over a plurality of the different time positions in accordance with a predetermined optimization method that optimizes the objectives of the dynamic controller to achieve a desired path, such that the objectives of the dynamic predictive model vary as a function of time.

26. The dynamic process controller of claim 25, wherein said dynamic predictive model comprises:

a dynamic forward model operable to receive variable input values at each of said time positions and map said variable input values to components of said dynamic predictive model associated with said received variable input values in order to provide a predicted dynamic controlled variable output value;

an error generator for comparing the predicted dynamic controlled variable output value to the desired controlled variable output value and generating a primary error value as the difference for each of said time positions;

an error minimization device for determining a change in the variable input value to minimize the primary error value output by said error generator;

a summation device for summing said determined variable input change value with an original variable input value, which original variable input value comprises the variable input value before the determined change therein, for a plurality of time position to provide a future variable input value as a summed input value; and

a controller for controlling the operation of said error minimization device to operate under control of said optimizer to minimize said primary error value in accordance with said optimization method.

27. A method for controlling operating process, comprising the steps of:

identifying variable input(s) and controlled variables associated with the process, wherein at least one variable input is a manipulated variable;

determining relationships between said variable input(s) and said controlled variables wherein said relationship comprises models, and wherein parameters within said model are dependent on said variable inputs; and

tuning said manipulated variable to achieve a desired controlled variable value.

28. The method of Claim 27, further including the step of determining the relationship between the variable inputs and the model parameters wherein said relationship comprises a model.

29. The method of Claim 27, wherein said step of identifying relationships between variable inputs and control variables utilizes neural networks.

30. The method of Claim 28, wherein said step of identifying relationship between the variable input(s) and dynamic model parameters utilizes neural networks.

31. The method of Claim 27, wherein said step of determining relationships between said variable input(s) and said controlled variable(s) utilizes a combination of physical models and empirical methods.

32. The method of Claim 31, wherein said physical models and empirical methods are combined in series.

33. The method of Claim 31, wherein said physical models and empirical methods are combined in parallel.

34. The method of Claim 31, wherein said physical model varies over an operating range.

35. The method of Claim 34, wherein said physical model is a function of said input parameters.

36. The method of Claim 35, wherein said physical model comprises first principle parameters which vary with said variable inputs, wherein empirical methods comprise a neural network used to identify first principle parameters values associated with said variable input(s), and wherein said neural network updates said first principle parameters with values associated with said variable input(s).

37. The method of Claim 36, wherein said neural network is trained.

38. The method of Claim 37, wherein said neural network is trained according to at least one method selected from the group consisting of gradient methods, back propagation, gradient-based nonlinear programming (NLP) methods, sequential quadratic programming, generalized reduced gradient methods, and non-gradient methods.

39. The method of Claim 38, wherein gradient methods require gradients of an error with respect to a weight and bias obtained by either numerical derivatives or analytical derivatives.